

Using Differential Privacy to Protect Earnings and Employment Statistics

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Any opinions and conclusions expressed herein are those of the author and do not represent the views of the U.S. Census Bureau. All results have been approved for disclosure. The PSEO disclosure avoidance methodology was approved by the Census Bureau Disclosure Review Board in release memo CBDRB-FY18-103.

What are Post-Secondary Employment Outcomes and Veteran Employment Outcomes?

Post-Secondary Employment Outcomes

- Partnership between Census Bureau and university systems or state longitudinal data systems
- Provides national earnings and employment outcomes by institution, degree and field

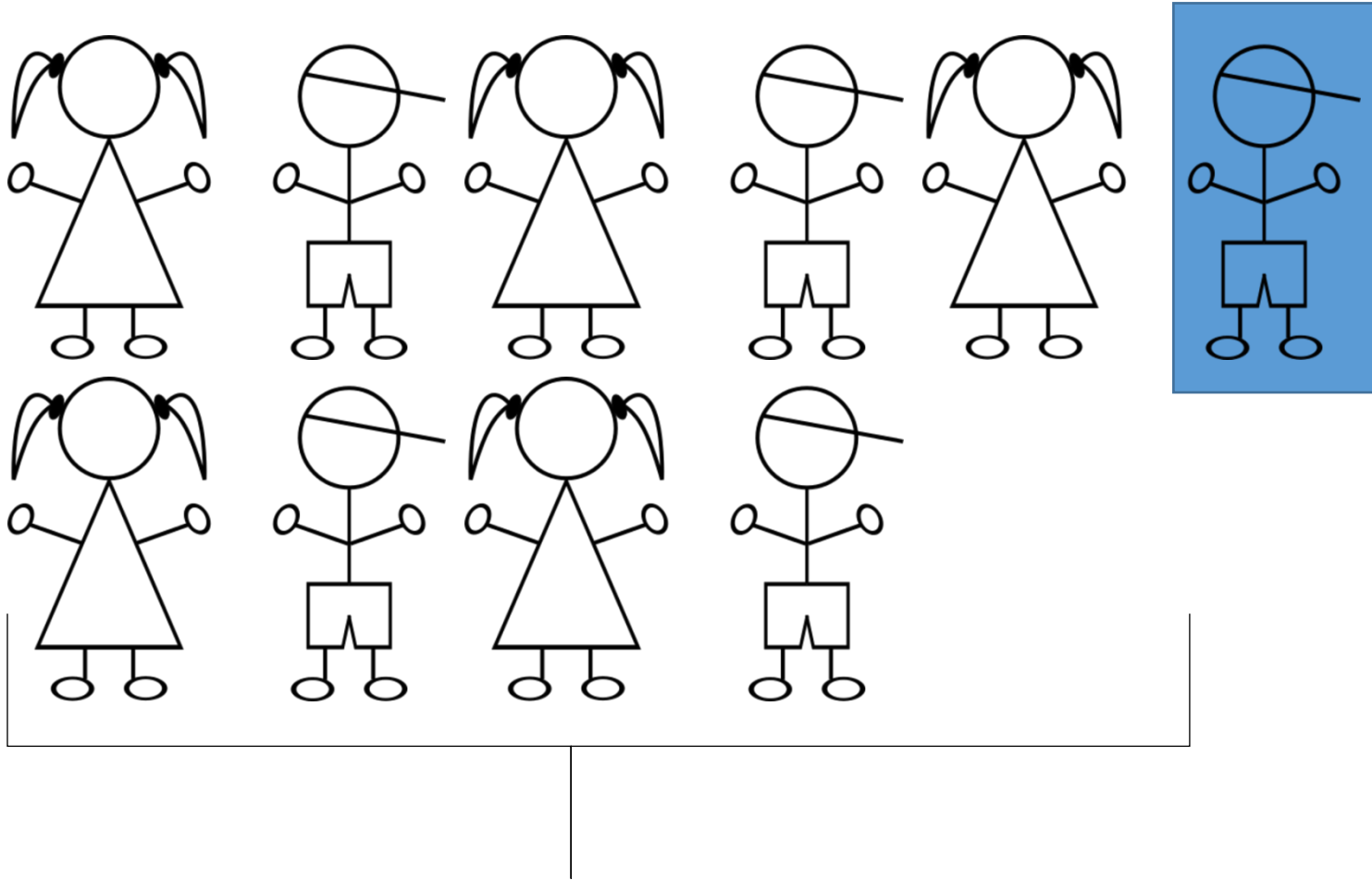
Veterans Employment Outcomes

- Partnership between Census and Army
- Provides national earnings and employment outcomes military specialization, service characteristics, employer industry (if employed), and veteran demographics

What are the threats to student privacy?

Protecting the Microdata

- Title 13 requirement:
 - The existence of a job held by an individual is confidential
- **We do not have a monopoly on microdata** – most of our partners have access to the frame (all graduates) and most of the earnings data we use to produce the statistics



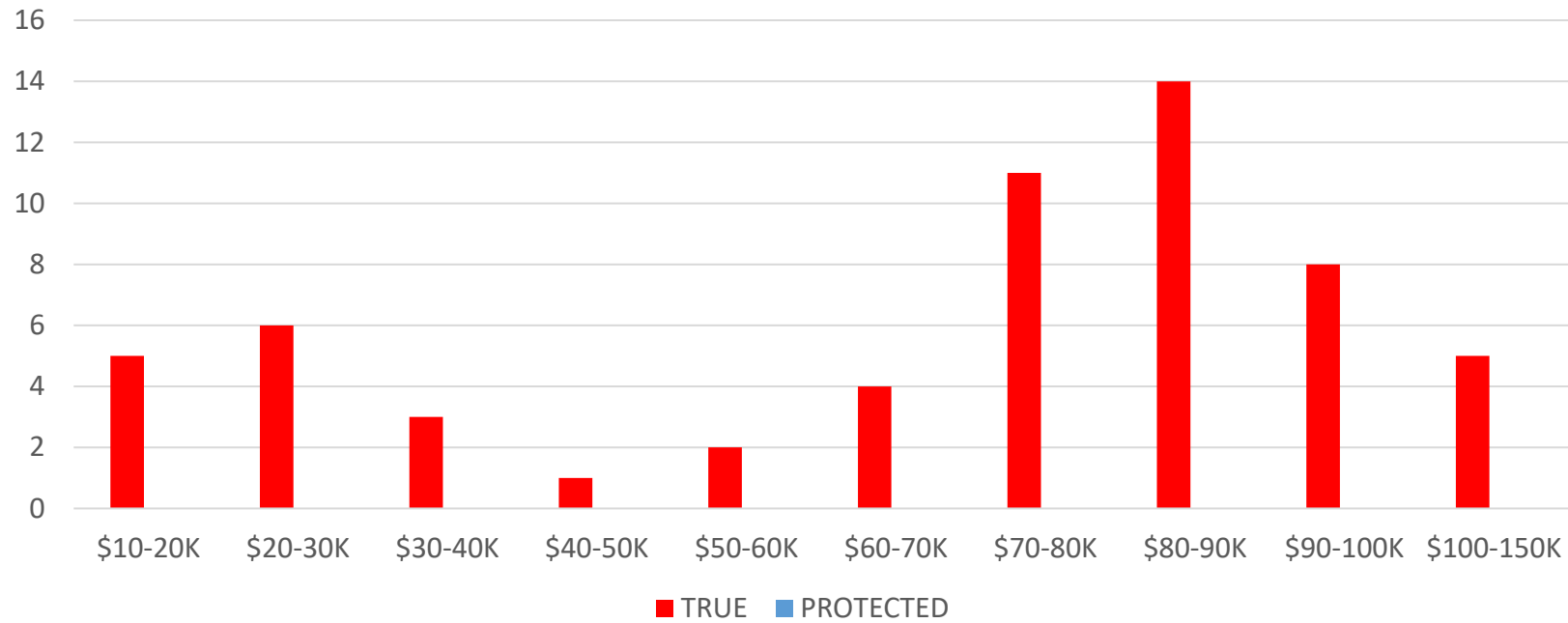
In-State Median Earnings: \$80,000

National Median Earnings: \$85,000

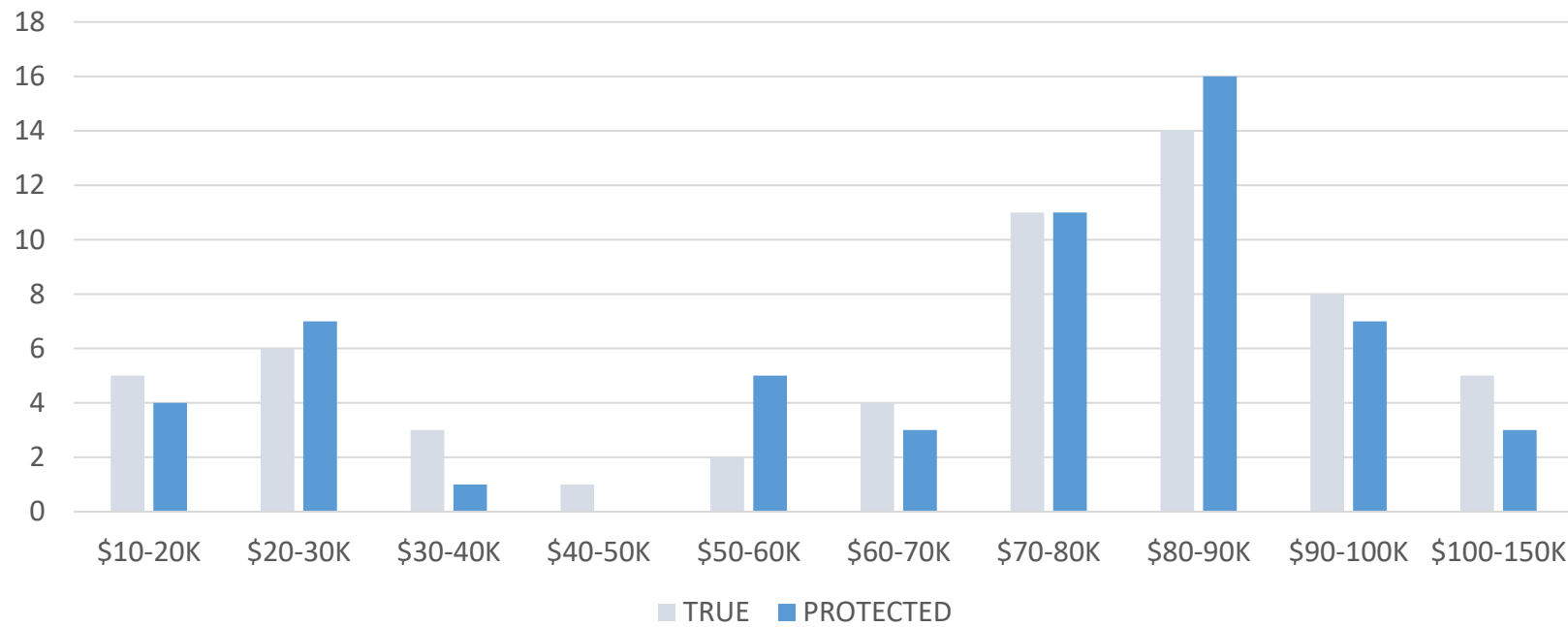
How we implement Differential Privacy

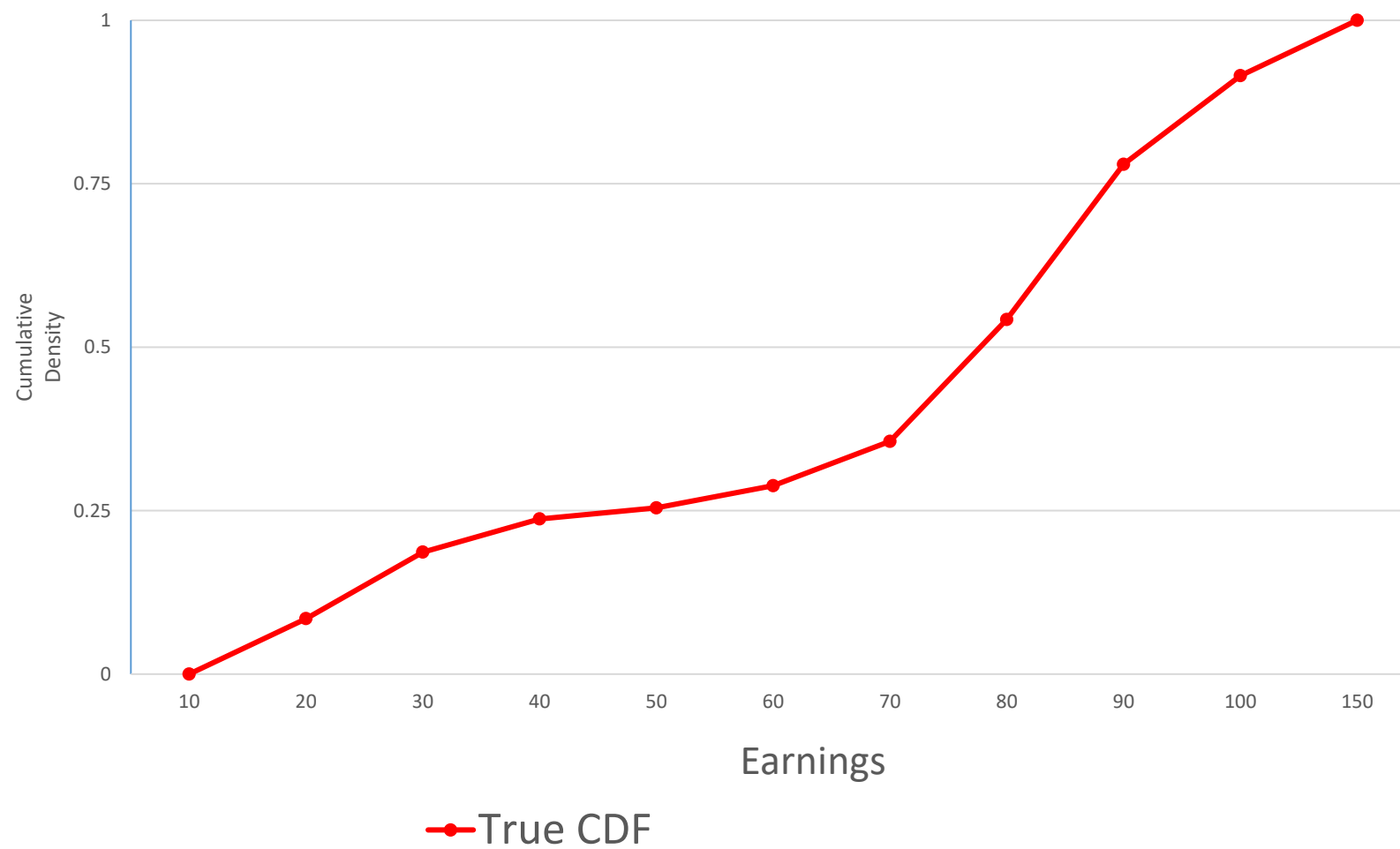
- Construct a histogram of earnings for each cell
 - Log-normal with parameters based on ACS public-use sample
 - Histogram bin ranges are public information
- Add geometric noise to each histogram bin
- Extract percentiles from the resulting protected CDF
- We use a total privacy loss budget of 3, half of which is used on the earnings tables
- Methodology described in Foote, Machanavajjala and McKinney (JPC 2019)

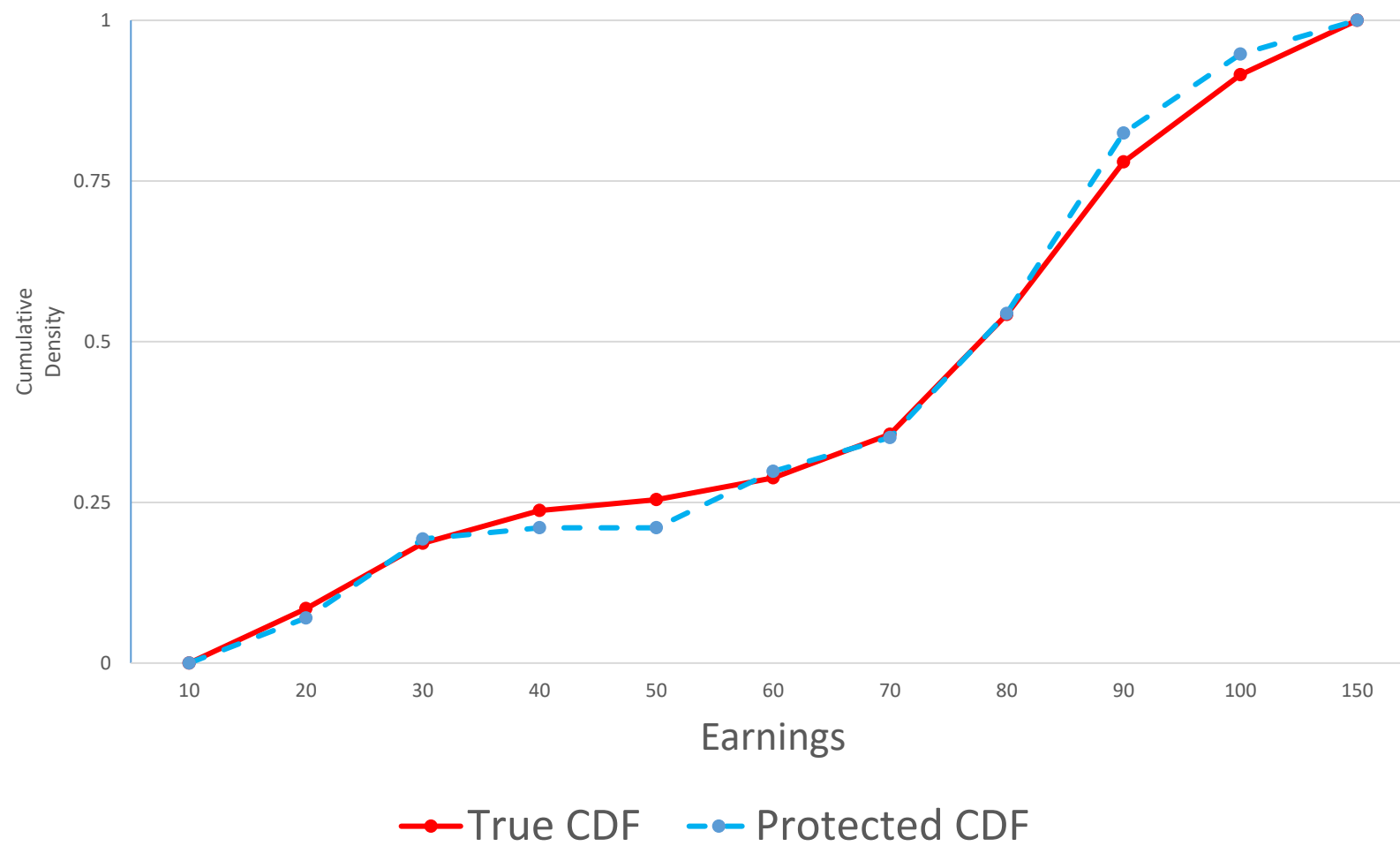
Simulated Data



Adding noise







Advantages of this DP implementation:

- We can aggregate to higher levels and calculate percentiles at those levels (for instance, median earnings at an institution)
- Easily implemented in other situations – Veterans Employment Outcomes used the same method, but with different histogram cutoffs
- Protection is intuitive for general public
- Code available for broader use (public on GitHub)

Table 1: Errors in Median Earnings, by Cell Size

Cell Size	Mean Absolute L1 Error	Mean Relative Error	L1 Error	
			10th Percentile	90th Percentile
30-50	2596	0.04714	-3584	4054
50-80	1526	0.0273	-2164	2344
80-100	1096	0.02108	-1642	1683
100-200	783	0.01461	-1193	1191
200-300	568	0.00925	-844	852
300+	344	0.00524	-523	506

Notes: Authors calculations.

Source: Foote, “Measuring Protection-Induced Errors in Earnings Outcomes from PSEO” (2021)

Questions?

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Code Here



Extra Slides

PSEO Output Tables

- **Graduate Earnings Table**

- 25th, 50th, and 75th percentiles of annual earnings for college and university graduates
- By degree level, degree major, and post-secondary institution
- One year, five years, and 10 years after graduation

- **Employment Flows Table**

- Employment by industry sector and Census Division of the country
- By degree level, degree major, and post-secondary institution
- One year, five years, and 10 years after graduation

How well does this protection system perform?

- We compare this protection system to two other candidates:
 - Evenly spaced bins
 - Smooth sensitivity (Nissim et al 2007)
- We measure relative accuracy:

$$RelAccuracy = 1 - \frac{|Protected - True|}{True}$$

- Choices for implementer: privacy loss; bin count

FIGURE 1. Relative Accuracy by Histogram Method, 50th Percentile

